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A Novel Energy-Aware Path Planning by Autonomous Underwater Vehicle in Underwater Wireless Sensor Networks

Sualtı Kablosuz Sensör Ağlarında Otonom Sualtı Aracı Tarafından Yenilikçi bir Enerji Farkında Yol Planlaması

Türk Denizcilik ve Deniz Bilimleri Dergisi
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ABSTRACT

Wireless sensor networks can monitor the environment to detect anomalies and reduce the risk of maritime traffic. Energy is necessary for low-power conditions where wireless sensor networks are used. Ensuring the lifespan of energy constraints and providing continuous environmental observation, data collecting, and communication requires management. Battery replacement and energy consumption issues can be resolved with path planning and energy-efficient autonomous underwater vehicle charging for sensor nodes. The nearest neighbour technique is used in this study to solve the energy-aware path planning problem of an autonomous underwater vehicle. Path planning simulations show that the nearest neighbour strategy converges faster and produces a better result than the genetic algorithm. We develop robust and energy-efficient path-planning algorithms that efficiently acquire sensor data while consuming less energy, allowing the monitoring system to respond to anomalies more rapidly. Increased sensor connectivity lowers energy usage and increases network longevity. This study also considers the situation when it is recommended to avoid taking direct travel paths between particular node pairs for a variety of reasons. This recommendation is considered in this study. We present a strategy based on a modified Nearest Neighbour-based Approach from the Nearest Neighbour method to address this more challenging scenario. The direct pathways between such nodes are constrained within the context of this technique. The modified version of Nearest Neighbor-based approach performs well even in that particular situation.

Keywords: Autonomous underwater vehicle; artificial intelligence; environmental monitoring; energy-aware path planning; wireless sensor networks; underwater communication

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ÖZET

Kablosuz sensör ağları, anormallikleri tespit etmek ve deniz trafiği riskini azaltmak için çevreyi izleyebilir. Kablosuz sensör ağlarının kullanıldığı düşük güç koşulları için enerji gereklidir. Enerji kısıtlamalarının ömrünün sağlanması ve sürekli çevresel gözlem, veri toplama ve iletişim sağlanması yönetim gerektirir. Pil değişimi ve enerji tüketimi sorunları, sensör düğümleri için yol planlaması ve enerji açısından verimli otonom su altı araç şarjı ile çözülebilir. Bu çalışmada, otonom bir su altı aracının enerji farkında yol planlama problemini çözmek için en yakın komşu tekniği kullanılmıştır. Yol planlama simülasyonları, en yakın komşu stratejisinin daha hızlı birleştiğini ve genetik algoritmadan daha iyi sonuç ürettiğini göstermektedir. Daha az enerji tüketirken sensör verilerini verimli bir şekilde toplayan ve izleme sisteminin anormalliklere daha hızlı yanıt vermesini sağlayan sağlam ve enerji açısından verimli yol planlama algoritmaları geliştiriyoruz. Artan sensör bağlantısı enerji kullanımını düşürür ve ağ ömrünü artırır. Bu çalışma ayrıca çeşitli nedenlerle belirli düğüm çiftleri arasında doğrudan seyahat yolları kullanmaktan kaçınılmasının önerildiği durumu da ele almaktadır. Bu öneri bu çalışmada dikkate alınmıştır. Bu daha zorlu senaryoyu ele almak için En Yakın Komşu yönteminden değiştirilmiş En Yakın Komşu tabanlı Yaklaşıma dayalı bir strateji sunuyoruz. Bu tür düğümler arasındaki doğrudan yollar bu tekniğin bağlamında kısıtlanmıştır. En Yakın Komşu tabanlı yaklaşımın değiştirilmiş versiyonu, o belirli durumda bile iyi performans gösterir.

Anahtar sözcükler: Otonom su altı aracı; yapay zeka; çevresel izleme; enerji bilinçli yol planlama; kablosuz sensör ağları; su altı iletişimi

1. INTRODUCTION

1.1. Motivation

Wireless sensor networks (WSN) are becoming increasingly important for resource exploration, navigation, and data collection due to their rapid expansion (Felemban *et al*., 2015). Intelligent Ocean Undersea Technology, or IoT, has been proposed recently (Qiu *et al*., 2020) and has a lot of potential uses. Many submerged sensor nodes transmit climate data to a data hub. Battery replacement for battery-operated nodes in extreme maritime circumstances necessitates costly and intricate technologies. Given limited energy capacity and short lifespan of underwater wireless sensor network (UWSN), energy efficiency must be increased to enhance UWSN performance and reliability. As a result of their short lifespan and limited energy source, UWSNs depend on increased energy economy for proper operation (Akyildiz *et al*., 2005).

The suggested metaheuristic-based path planning technique for WSN accelerates sensor data collecting while saving energy, enabling faster monitoring system reaction to ship disaster hazards. By getting closer to the sensors, you can communicate with them and use less energy. WSN will therefore last longer, monitoring the environment to detect anomalies and prevent accidents.

Numerous studies have been conducted on this issue. Wireless sensor networks (WSNs) use a lot of energy to transmit data. Energy consumption and transmission are reduced by optimising and compressing sensory data (Li *et al*., 2020). Furthermore, by strategically placing and routing nodes, UWSN energy efficiency can be raised. By streamlining the deployment and routing procedures, energy consumption can be decreased and network lifetime can be extended. This is because there may be variations in the energy usage and distance between data sensor nodes (Cheng *et al*., 2014).

Even with these techniques, replacing the battery when it runs low is still important. Energy transfer technology can be used to charge underwater sensors so they can be used for long-term monitoring and data transmission without the need for new batteries (Khan *et al*., 2018). Through addressing high water pressure and short circuits, the team (Pendergast *et al*., 2011) produced a rechargeable lithium-ion battery module that may be used underwater. Due to limitations on the distance over which energy can be transferred, autonomous underwater vehicles require help planning their routes and charging. An autonomous underwater vehicle, or AUV, is a self-propelled submersible that can do moderate activities without the need for human help (Blidberg *et al*., 2001). Underwater research, environmental monitoring, and marine safety have all made extensive use of AUVs because to their affordability and security in seabed inquiry, search, identification, and rescue (Ghafoor *et al*., 2019). The AUV's constrained charging space and power carrying capabilities make data loss from subsequent nodes troublesome. Therefore, it is difficult to guarantee that the AUV would be advantageous for broader detection zones, especially in maritime conditions.

1.2. Main Contributions

The main contribution can be briefed as follows:

- This paper offers a comparative examination of AI-based techniques for three-dimensional path planning for autonomous underwater vehicles (AUV). The main focus of the presentation is the challenges that arise when collecting data in wireless sensor networks.
- The Nearest Neighbour (NN)-based Approach is recommended as a workable solution for the three-dimensional path planning problem. This technique considers the current computer limitations during the procedure.
- We introduce a modified Nearest Neighbour-based Approach, which modifies the Nearest Neighbour algorithm to avoid obstacles in the three-dimensional path planning issue. The travelling restrictions between certain sensor pairs are considered whenever this technique is used.
- Our approach provides not only an energy-efficient but also computationally efficient and fast solution.

1.3. Organization

The remainder of the paper will follow this format. A succinct synopsis of pertinent studies from the literature is given in Part 2. In Section 3, the issue is outlined and a system model is supplied. A few methods for solving the 3D path planning problem are shown in Section 4. In Section 5, we propose a novel solution to the problem with some limitations between some of the sensor pairs. We evaluate effectiveness of the proposed strategies in Section 6. Section 7 concludes the work. Section 8 gives future work.

2. RELATED LITERATURE

This section considers the necessary literature to address path planning in WSN. Energy-efficient communication techniques must be created as alternatives because of battery limitations. Lee et al. looked at network topology-based energy-efficient WSN MAC techniques. As in the works (Le *et al*., 2011, Zenia *et al*., 2016) investigate secure and energy-conserving WSN MAC and routing techniques. (Khan *et al*., 2019) presents a packet-sending strategy that aims to improve channel quality and decrease redundancy. The hybrid-coding-aware routing technique created by a work (Su *et al*., 2023) has applications for underwater acoustic sensor networks (UASNs). This method reduces gearbox overhead and increases reliability.

Clustering improves resource management, energy efficiency, longevity, and data aggregation in wireless sensor networks (Kumar *et al*., 2018). To reduce unnecessary transfers inside the network, a cluster head (CH) disseminates information throughout each cluster (Xie *et al*., 2013). Energy and bandwidth reductions are attainable at challenging fields with restricted communication resources (Yadav *et al*., 2019).

Using a clustering-based communication protocol, the work (Sun *et al*., 2022) reduced the energy usage of sensor nodes. The topology management system developed by Jin et al. guarantees reliable connectivity while simultaneously improving coverage and longevity (Fan *et al*., 2023). Liu *et al*. (2019) developed a virtual force-based distributed node deployment technique to expand WSN network coverage. In Wei *et al*. (2020), a network topology control model that prolongs network lifetime qualities such resilience, energy consumption balance, and topology is presented.

It improves data transmission while doing so.
AUVs charge and collect data concurrently with the UAV. AUVs equipped with sensors can collect data on marine life, geology, and water quality. AGV assisted communication was tested in (Zhu *et al*., 2023), where the AUV was employed as a mobile node to gather energy-saving data. For data gathering and K-means path planning, AUVs were proposed in (Yan *et al*., 2023), and (Shen *et al*., 2020). AUVs are used for two purposes: data collection and multi-hop detection (Gjanci *et al*., 2017, Yan *et al*., 2018).
AUVs may network and communicate underwater. AUVs or central stations can receive data from mobile or fixed sensors. The activities can be managed in real time. Kan *et al*. (2018) field-deployable three-phase wireless charging system offers quick and easy AUV charging. According to Ramos *et al*. (2018), using dynamic system theory for AUV navigation at depths of 0–100 m resulted in a faster battery life.
Building battery-charging, autonomous docking AUVs allow for continuous operation without requiring human intervention. The dock charges the batteries in the AUVs and the sensor nodes. Their efficiency and independence increase in the absence of retrieval and recharging. The efficiency of the AUV path design is increased. Cheng et al. apply kinematic and dynamical models to plan AUV routes, avoid obstacles, and evaluate energy usage for energy savings and network longevity (Cheng *et al*., 2021). The work (Kumar *et al*., 2021) have presented a hybrid underwater AUV exploration strategy that drastically reduces its range. Using data collecting points, the exploring region is subdivided in (Golen *et al*., 2010). Prepared paths save AUV energy during data collection. Rechargeable method increases network life (Yhi *et al*., 2022).

3. SYSTEM MODEL AND PROBLEM DEFINITION

Our research focusses on the energy-aware path planning problem for an AUV's sensor visit. We define this challenge and provide an illustrative case. We examine the UWSN system model first. The energy-aware path planning problem is then defined more precisely.

3.1. System Model

In this network system, every sensor node sends data to the cluster head node using a wireless network. Magnetic resonance coupling AUVs charge each sensor node before returning to a charge station (CS) for resting and data gathering.
The maintenance of energy consumption balance in sensors is a critical consideration for Wireless Sensor Networks (WSNs). autonomous underwater vehicle (AUV) collect data from several studies (Pop *et al*., 2024, Davendra, 2010, Johnson *et al*., 1997) to examine and address discrepancies in energy usage. The AUV methodically visits each sensor node according to a pre-established plan to ensure an equitable distribution of energy usage.

3.2. Problem Definition

The difficulty of optimising energy consumption in path planning using AUV is classified as the travelling salesman problem (TSP) (Pop *et al*., 2024, Davendra, 2010, Johnson *et al*., 1997). The TSP is commonly solved using classical search algorithms and evolutionary algorithms, which are the primary approaches used in this procedure. The artificial potential field technique, greedy algorithm, and quick progress algorithm are all examples of algorithms that fall within the previously mentioned category. The latter group includes techniques such as genetic algorithm and nearest neighbour algorithm, which are derived from biological algorithms.

4. PROPOSED ENERGY-AWARE PATH PLANNING (EAPP) APPROACHES

This section focuses on the challenge of energy-conscious path planning for an AUV. The primary area of concern is the separation between each pair of sensor nodes. The TSP is widely recognised as the most prominent NP-hard optimisation problem (Davendra, 2010, Johnson *et al*., 1997). The TSP aims to construct an optimised itinerary for a salesperson, starting from his apartment, visiting many places, and returning to the starting point, to decrease travel time (Gutin *et al*., 2002).
By considering the EAPP problem as a TSP

problem, we propose three approaches: Nearest Neighbour (NN)-based Approach, the Grey Wolf Optimiser (GWO)-based Approach, and the Genetic Algorithm (GA)-based Approach.

4.1. Nearest Neighbour (NN)-Based Approach

Concurrently, we suggest employing the Nearest Neighbour Algorithm (Gutin *et al*., 2007) to address the EAPP problem by seeing it as a Travelling Salesman Problem (TSP).

4.2. Grey Wolf Optimizer (GWO)-based Approach

Our methodology consists of tackling the EAPP issue by seeing it as a Travelling Salesman Problem (TSP) and creating a solution for 3D path planning using the Grey Wolf Optimiser Algorithm (Mirjalili *et al*., 2014). To do this, we have formulated a solution.

4.3. Genetic Algorithm (GA)-based Approach

To address the EAPP issue, also referred to as the TSP, we offer a solution that employs the Genetic Algorithm. This technique is specifically tailored for planning paths in three-dimensional space (Goldberg, 1989, Bonabeau *et al*., 1999). Genetic algorithms are designed to address complex optimization problems by simulating the processes of biological evolution. This is done to address optimal issues. To address the issues of the Travelling Salesman Problem (TSP), a genetic algorithm is used. This approach begins by identifying the people that make up the TSP solution and initializing the population. These stages signify the beginning phase of the procedure. Throughout the genetic processes of selection, crossover, and mutation, individuals in the population are evaluated based on a fitness function. Individuals who have been identified as the most physically competent are selected. The maximum number of iterations is the decisive parameter that will determine the termination of the GA. In this study, individual fitness is assessed by either the overall distance travelled or the total amount of energy used by the AUV. Both factors are taken into account.

5. MODIFIED NEAREST NEIGHBOUR-BASED APPROACH

This section focuses on the problem of energy-efficient path planning, considering the constraints imposed by specific sensor pairs that are located close to each other. Placing barriers between sensors may obstruct the direct transfer of data between them. The AUV has multiple reasons for avoiding a straight transition between the first and second sensors. Each of these elements will be expounded upon in more detail below. These considerations include potential hazards, obstructed paths, such as those covered in mud, between the two sensors, and temperatures that constantly vary. In this specific case, the AUV will move towards a sensor or sensors positioned between the two sensors.

Our proposed solution to the problem of three-dimensional path planning is the modified version of Nearest Neighbour-based Approach proposed in the works (Gul *et al*., 2024, Gul, 2024). This technique aims to address minor barriers that frequently occur in the space between certain pairs of sensors.

$$\boldsymbol{D} = \begin{bmatrix} \boldsymbol{d_{11}} & \boldsymbol{d_{12}} & \cdots & \boldsymbol{d_{1(n-1)}} & \boldsymbol{d_{1n}} \\ \boldsymbol{d_{21}} & \boldsymbol{d_{22}} & \cdots & \boldsymbol{d_{2(n-1)}} & \boldsymbol{d_{2n}} \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ \boldsymbol{d_{(n-1)1}} & \boldsymbol{d_{(n-1)2}} & \cdots & \boldsymbol{d_{(n-1)(n-1)}} & \boldsymbol{d_{(n-1)n}} \\ \boldsymbol{d_{n1}} & \boldsymbol{d_{n2}} & \cdots & \boldsymbol{d_{n(n-1)}} & \boldsymbol{d_{nn}} \end{bmatrix} \quad \textbf{(1)}$$

If some obstacles or obstructions hinder movement from node $\boldsymbol{n-1}$ to node $\boldsymbol{n}$, then the distance between node $\boldsymbol{n-1}$ and node $\boldsymbol{n}$, denoted by $\boldsymbol{d_{(n-1)n}}$ is assigned a value of $\boldsymbol{M}$, where $\boldsymbol{M}$ denotes a considerably large number.

The distance cost matrix $\boldsymbol{D^{OA}_{mod}}$, which is updated prior to using the Nearest Neighbour approach for $\boldsymbol{n}$ nodes, can be constructed by assigning a large integer value $\boldsymbol{M}$ to the entry $\boldsymbol{d_{(n-1)n}}$.

$$D_{mod}^{OA} = \begin{bmatrix} d_{11} & M & \cdots & d_{1(n-1)} & d_{1n} \\ d_{21} & d_{22} & \cdots & d_{2(n-1)} & d_{2n} \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ d_{(n-1)1} & d_{(n-1)2} & \cdots & d_{(n-1)(n-1)} & M \\ d_{n1} & d_{n2} & \cdots & d_{n(n-1)} & d_{nn} \end{bmatrix} \quad (2)$$

Using the updated distance cost matrix D_{mod}^{OA}, we implement the 3D Nearest Neighbour algorithm. Thus, we have proposed a modified Nearest Neighbour approach.

6. NUMERICAL RESULTS

This section assesses the effectiveness of algorithms used to solve the 3D energy-aware path planning problem of an AUV. The decisive factor is the distance separating each pair of sensor nodes. Through the random deployment of sensor nodes, we were able to establish a three-dimensional zone with dimensions of 500 meters in length, breadth, and height. This enabled us to carry out the simulations. The selected works utilised a range of dimension lengths and distances that were in line with our approach.

6.1. 50-node scenario

This article specifically examines the quantitative evaluation of the proposed algorithms in a particular scenario involving a single AUV and 50 nodes. Figure 1 illustrates the configuration of 50 nodes in a three-dimensional space, with each dimension measuring 500 m.
Locations are given as ((442, 22, 474), (502, 59, 327), (285, 291, 67), (294, 311, 108), (57, 149, 390), (454, 22, 47), (238, 383, 180), (425, 11, 18), (159, 463, 38), (77, 30, 452), (143, 74, 155), (292, 356, 348), (4, 215, 113), (148, 179, 127), (158, 209, 285), (448, 263, 362), (108, 141, 230), (450, 484, 172),(428, 112, 223), (489, 281, 23), (259, 242, 186), (325, 162, 227), (141, 22, 386), (296, 108, 402), (414, 355, 411), (439, 62, 14), (241, 7, 29), (258, 272, 221), (319, 390, 244), (209, 299, 390), (169,156, 443), (150, 465, 96), (187, 105, 280), (272, 447, 28), (348, 263, 305), (389, 234, 382), (399, 416, 213), (31, 370, 63), (152, 120, 371), (207, 67, 491), (118, 352, 126), (225, 361, 460), (460, 203, 139), (15, 100, 244), (340, 188, 20), (60, 447, 316), (430, 154, 168), (214, 158, 283), (210, 332, 95), (102, 335, 422)).

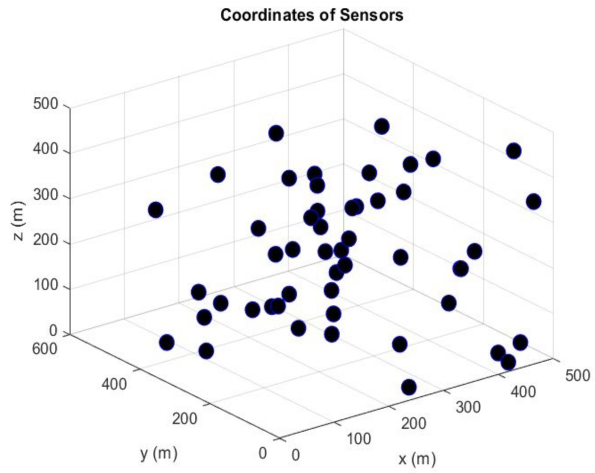

Figure 1. Locations of sensors

We evaluate the efficacy of Nearest Neighbour (NN), Grey Wolf Optimiser Algorithm (GWO), and Genetic Algorithm (GA)-based Approaches by analysing different combinations of these parameters.

6.1.1. NN-based Approach

This subsection evaluates performance of an NN-based solution. Figure 2 demonstrates the NN's achieved path planning solution in a scenario in Figure 1.

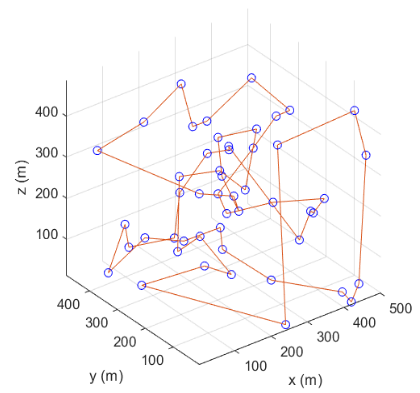

Figure 2. Achieved (6293 m) path planning solution by Nearest Neighbor

6.1.2. GA-based Approach

This subsection evaluates performance of an GA-based solution. Figure 3 demonstrates the GA's achieved path planning solution in 1000 iterations in a scenario in Figure 1.

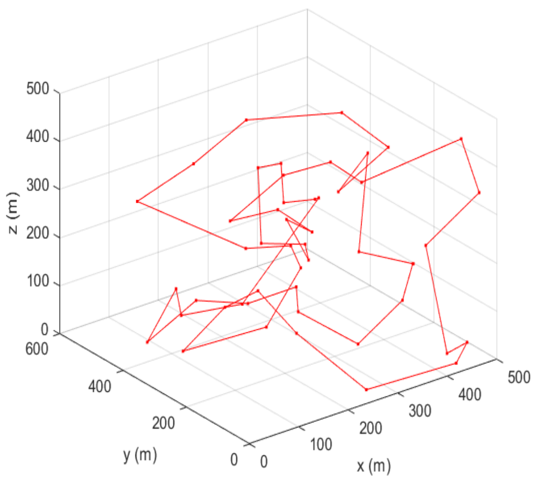

Figure 3. Achieved (6198 m) path planning solution with GA in 1000 iterations

6.1.3. GWO-based Approach

This subsection evaluates performance of an GWO-based solution. Figure 4 demonstrates the GWO's achieved path planning solution in 1000 iterations in a scenario in Figure 1.

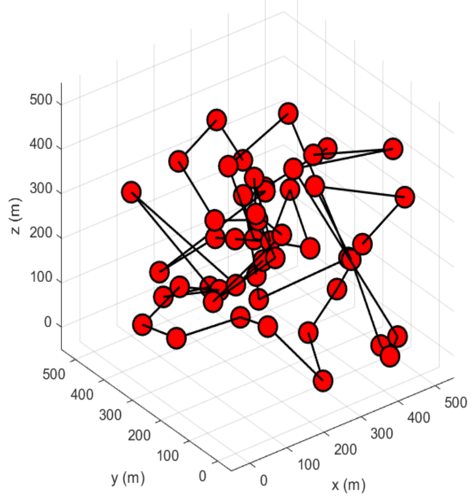

Figure 4. Achieved (8788 m) path planning solution with GWO in 1000 iterations

6.1.4. Discussion

In general, NN-based Approach achieves shorter path than GA-based Approach.

Figure 5 illustrates the total distance travelled by AUV employing multiple algorithms (NN Based Approach, GWO Based Approach, and GA Based Approach) to visit the 50 sensor nodes shown in Figure 1. Based on the data presented in Figure 5, we can make the following inferences about the performance of the algorithms in the scenario involving 50 nodes. According to the general pattern, the NN-based method and GA-based approach are more effective than the GWO-based approach. The neural network-based approach demonstrates superior performance compared to the genetic algorithm-based approach in terms of results up to the 500th iteration. In addition, the NN-based Approach is significantly faster in solving the problem, taking only 0.094679 seconds compared to the GA-based approach's time of 3.598634 seconds (38 times faster).

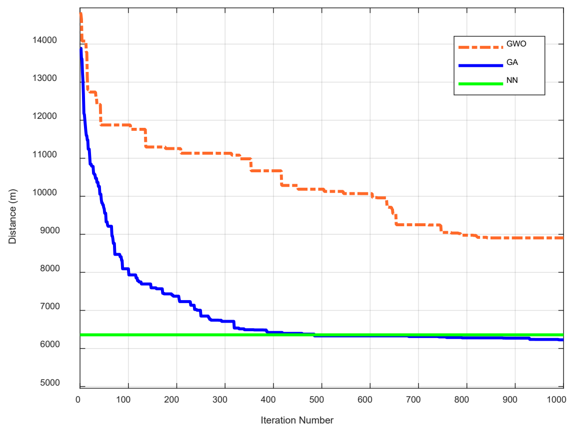

Figure 5. Achieved path lengths for visiting 50 nodes by NN, GWO, and GA-based Approaches

Figure 5 enables us to derive the following conclusions. Although the NN-based strategy quickly found a solution of around 6.27 km, both the GA-based method and the GWO-based approach initially had longer road lengths of 15 km in the first iteration. The GA-based strategy outperforms the GWO-based technique significantly at the 100th iteration, achieving a distance of 2.90 Km, which is 30% less. The NN strategy performs better than the GWO and GA strategies at the 300th iteration. The GA strategy achieves superior performance compared to the NN approach at the 600th iteration. Although the NN-based technique offers a speedier and more practical solution, it does not provide a shorter path compared to other methods. At the 1000th iteration, the GA-based technique significantly beats GWO-based approaches, with a performance of 2510 m, which is 28.5% lower than the GWO-based approach.

6.2. 100-node scenario

This article specifically examines the quantitative evaluation of the proposed algorithms in a particular scenario involving a single AUV and 100 nodes. Figure 6 illustrates the configuration of 100 nodes in a three-dimensional space, with each dimension measuring 500 m.

Locations are given as ((410, 84, 325), (455, 400, 192), (66, 158, 408), (459, 267, 269), (319, 85, 178), (51, 303, 472), (142, 134, 440), (276, 330, 278), (481, 347, 314), (485, 377, 296), (81, 228, 106), (488, 44, 153), (481, 117, 238), (245, 459, 118), (403, 79, 425), (73, 415, 100), (213, 272, 115), (460, 501, 88), (399, 42, 116), (482, 224, 220), (330, 56, 158), (20, 483, 464), (427, 5, 218), (469, 390, 95), (342, 411, 455), (381, 437, 492), (374, 45, 222), (199, 202, 58), (330, 132, 132), (88, 403, 207), (356, 218, 300), (18, 458, 134), (141, 93, 304), (26, 134, 358), (51, 75, 113), (414, 71, 61), (350, 437, 151), (161, 292, 162), (478, 277, 215), (20, 75, 256), (222, 429, 45), (193, 314, 134), (385, 178, 403), (400, 259, 17), (96, 203, 467), (247, 40, 368), (225, 122, 247), (326, 64, 292), (357, 94, 121), (380, 122, 232), (141, 211, 484), (342, 27, 276), (330, 454, 263), (84, 475, 118), (62, 248, 247), (252, 247, 315), (482, 171, 342), (173, 453, 200), (295, 187, 186), (114, 58, 496), (378, 393, 21), (130, 197, 445), (255, 123, 459), (352, 204, 401), (448, 51, 52), (482, 68, 133), (276, 474, 170), (72, 481, 342), (77, 290, 71), (131, 32, 363), (423, 120, 56), (130, 179, 329), (410, 413, 250), (124, 10, 392), (467, 24, 360), (177, 87, 454), (101, 327, 448), (128, 368, 170), (311, 326, 352), (239, 228, 101), (178, 276, 18), (418, 151, 375), (295, 375, 253), (277, 97, 242), (461, 346, 455), (145, 94, 307), (381, 187, 311), (379, 315, 432), (193, 393, 405), (286, 43, 291), (40, 467, 94), (29, 390, 122), (268, 246, 446), (392, 220, 17), (470, 226, 247), (67, 156, 86), (287, 257, 492), (237, 258, 359), (8, 411, 253), (171, 400, 238)).

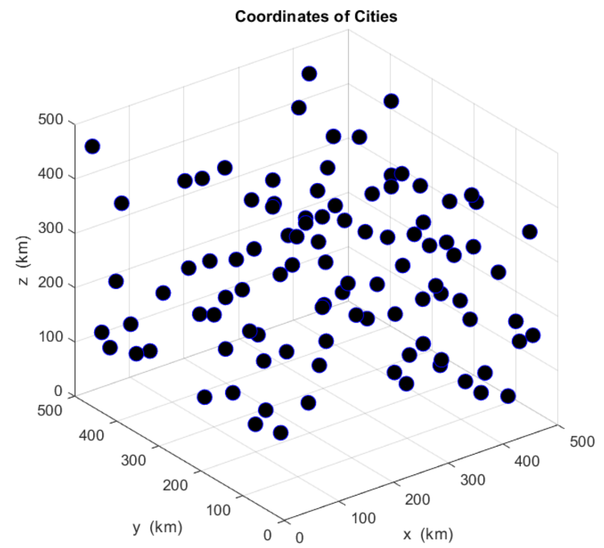

Figure 6. Locations of sensors

We evaluate the efficacy of Nearest Neighbour (NN), Grey Wolf Optimiser Algorithm (GWO), and Genetic Algorithm (GA)-based Approaches by analysing different combinations of these parameters.

6.2.1. NN-based Approach

This subsection evaluates the performance of an NN-based solution. Figure 7 demonstrates the NN's achieved path planning solution in a scenario in Figure 6.

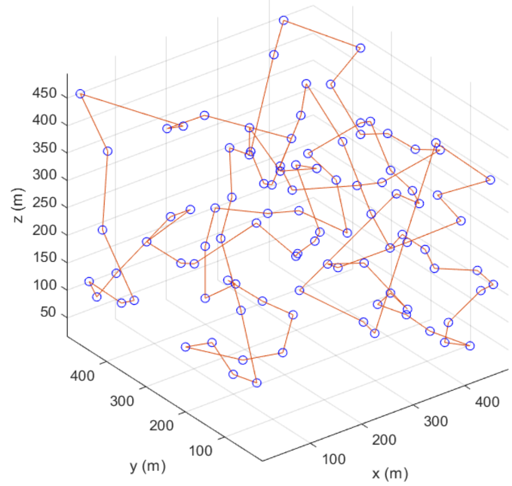

Figure 7. Achieved (9046 m) path planning solution by Nearest Neighbor

6.2.2. GA-based Approach

This subsection evaluates performance of an GA-based solution. Figure 8 demonstrates the GA's achieved path planning solution in 1000 iterations in a scenario in Figure 6.

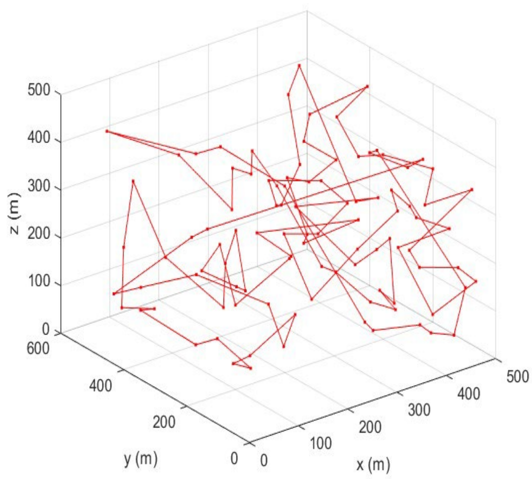

Figure 8. Achieved (11441 m) path planning solution with GA in 1000 iterations

6.2.3. GWO-based Approach

This subsection evaluates performance of an GWO-based solution. Figure 9 demonstrates the GWO's achieved path planning solution in 1000 iterations in a scenario in Figure 6.

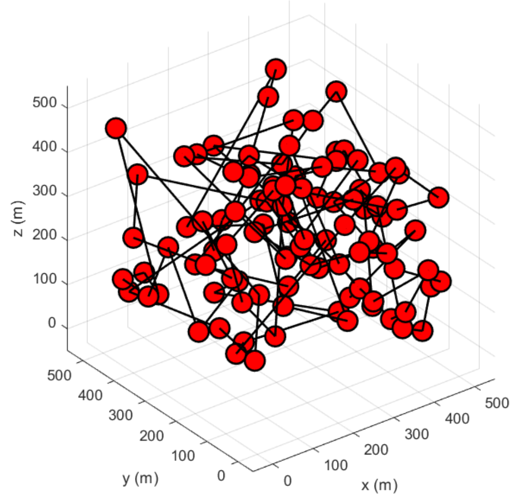

Figure 9. Achieved (17686 m) path planning solution with GWO in 1000 iterations

6.2.4. Discussion

In general, NN-based Approach achieves shorter path than GA-based Approach.

Figure 10 illustrates the total distance travelled by AUV employing multiple algorithms (NN Based Approach, GWO Based Approach, and GA Based Approach) to visit the 100 sensor nodes shown in Figure 6. Based on the data presented in Figure 10, we can make the following inferences about the performance of the algorithms in the scenario involving 100 nodes. According to the general pattern, the NN-based method and GA-based approach are more effective than the GWO-based approach. The neural network-based approach demonstrates superior performance compared to the genetic algorithm-based approach in terms of results up to the 500th iteration. In addition, the NN-based Approach is significantly faster in solving the problem, taking only 0.094679 seconds compared to the GA-based approach's time of 3.508634 seconds (37 times faster).

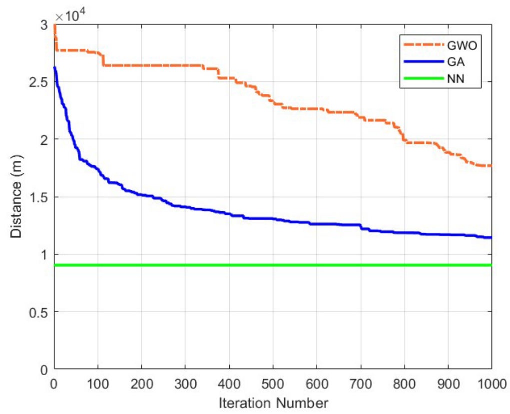

Figure 10. Achieved path lengths for visiting 100 nodes by NN, GWO, and GA-based Approaches

Figure 10 enables us to derive the following conclusions. Although the NN-based strategy quickly found a solution of around 9.05 km, both the GA-based method and the GWO-based approach initially had longer road lengths of 27 km and 30 km in the first iteration. The GA-based strategy outperforms the GWO-based technique significantly at the 100th iteration, achieving a distance difference of 10.07 Km, which is 36.6% less. The NN strategy performs better than the GWO and GA strategies at the 400th iteration where GA strategy achieves 13500 m, nearly half of the path achived by GWO approach 25294 m (46.6% difference with 11794 m). With a distance of 12369 m, the GA strategy keeps its superior performance compared to the GWO approach with 21879 m at the 700th iteration (43.42% difference with 9510 m). The NN-based technique offers not only a speedier and more practical solution but also it provides a shorter path compared to other methods. At the 1000th iteration, the GA-based technique with 11440 m achieved distance significantly beats GWO-based approach with 17686 m, with a performance of 6246 m, which is 35.3% lower than the GWO-based approach.

6.3. Obstacle Avoidance scenario

We evaluate the efficacy of the modified Nearest Neighbor-based method for solving the 3D TSP problem. However, we impose a constraint that makes it prohibitively expensive and impractical to visit node i immediately after node $i-1$.

6.3.1. Modified NN-approach with 50 nodes

This subsection examines the solution to the 3D TSP issue using the modified Nearest Neighbour approach. The path planning solution generated by modified NN for visiting 50 nodes depicted in Figure 1 is illustrated in Figure 11.

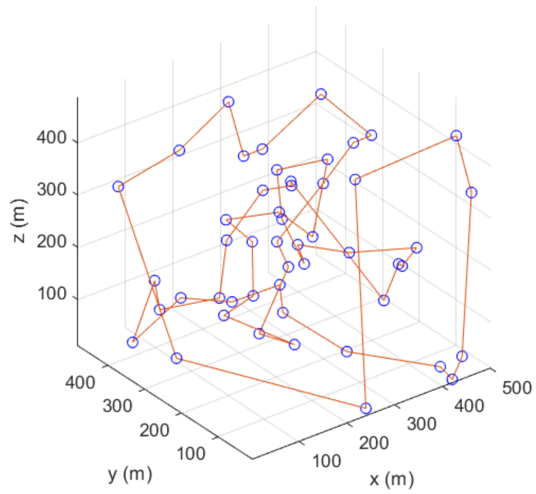

Figure 11. Achieved path planning solution for visiting the 50 nodes by AUV with modified NN under limitations

6.3.2. Modified NN-approach with 100 nodes

This subsection examines the solution to the 3D TSP issue using the modified Nearest Neighbour approach. The path planning solution generated by modified NN for visiting 100 nodes depicted in Figure 6 is illustrated in Figure 12.

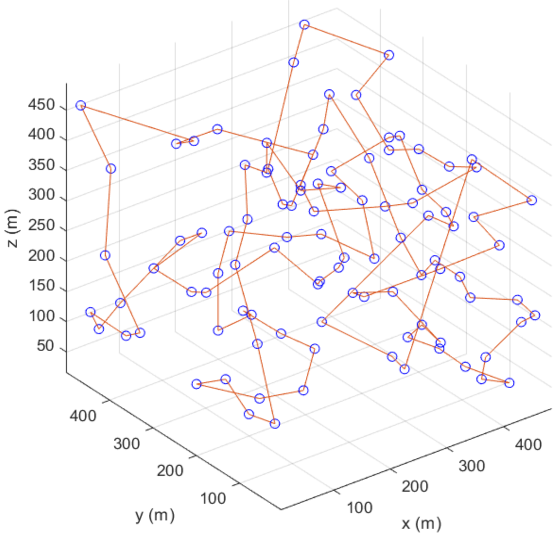

Figure 12. Achieved path planning solution for visiting the 100 nodes by AUV with modified NN under limitations

6.3.3. Discussion

Taking into consideration the overall trend, the NN-based Approach outperforms the modified NN-based Approach. Table 1 shows the total distance travelled by AUV utilising NN-based Approach and modified NN-based Approach under the 50-node scenario in Figure 1 and the 100-node scenario in Figure 6.

We can infer the following conclusions from Table 1. Under the 50-node situation, NN-based approach and modified NN-based Approach achieve virtually comparable performance, with only a slight deviation (134 m, or 2.04\% less than modified NN-based technique). Under the 100-node situation, the NN-based approach and modified NN-based Approach achieve virtually comparable performance, with only a slight deviation (18 m, or 0.2\% less than the modified NN-based technique).

7. CONCLUSION

Research is concentrating on longer and wider exploratory ranges as environmental monitoring becomes increasingly important. Using an autonomous underwater vehicle with a limited battery pack, we theoretically evaluate the energy consumption of the wireless sensor network (WSN) and propose an efficient path-planning strategy for charging it. The WSN has limited energy, therefore we concentrate on charging. To extend the exploration network, many AUVs efficiently charge the WSN. It is possible to significantly increase exploration range and charge efficiency by selecting appropriate diving places and building a path that takes the node's location and data flow into account.

Table 1. Total distance by NN-based Approach and OANN-based Approach under 50-node and 100-node scenarios.

Iteration	Achieved Length
NN with 50 nodes	6322 (m)
Modified NN with 50 nodes	6456 (m)
NN with 100 nodes	9045 (m)
Modified NN with 100 nodes	9063 (m)

Data collection problems for AUVs can be handled using Nearest Neighbour, Grey Wolf Optimiser, and Genetic Algorithm approaches. Based on simulations, the AUV route planning system finds a better solution and converges more quickly than previous algorithms by using Nearest Neighbour.

A physical constraint or obstacle that renders visiting node $\boldsymbol{i}$ soon after node $\boldsymbol{i-1}$ impractical owing to large distance costs is the basis for the Obstacle-Avoided Nearest Neighbour-based solution for the 3D TSP problem. Even yet, the Obstacle-Avoided Nearest Neighbour-based method functions similarly.

8. FUTURE WORKS

In the future, this research can be extended in the following ways. In addition to underwater communication networks, autonomous vehicles for data collection are widely used in the framework of terrestrial wireless sensor networks. The research works (Gul *et al.*, 2020, Gul *et al.*, 2022, Gul *et al.*, 2023, Gul *et al.*, 2024) have investigated data gathering problem from clustered robotic and wireless sensor networks, hence reducing the energy consumption of cluster heads by considering a UAV with limited battery capacity. In underwater communication networks, the data gathering problem can be investigated with autonomous underwater vehicle with a limited battery capacity.

As another future work, we can tackle the problem by considering the energy harvesting models and approaches in the works (Eriş *et al*., 2023, Eriş *et al*., 2024a, Eris *et al*., 2024b).

In the future, we can also tackle the problem by considering more realistic models about the mission, function and working principle of autonomous underwater vehicles.

AUTHORSHIP CONTRIBUTION STATEMENT

Ömer Melih GÜL: Conceptualization, Methodology, Validation, Formal Analysis, Resources, Writing - Original Draft, Writing-Review and Editing, Data Curation, Software, Visualization, Supervision, Project administration, Funding acquisition.

CONFLICT OF INTERESTS

The author(s) declare that for this article they have no actual, potential or perceived conflict of interests.

ETHICS COMMITTEE PERMISSION

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